Accuracy of the Home Energy Saver Energy Calculation Methodology

Danny Parker

Florida Solar Energy Center

Evan Mills, Leo Rainer, Norm Bourassa, and Greg Homan

Lawrence Berkeley National Laboratory

Presented at the 2012 ACEEE Summer Study on Energy Efficiency in Buildings, Asilomar, CA August 13-17



The Home Energy Saver Suite

- LBNL creates in early 1990s
- First web-based residential energy analysis tool
- Operational assessment (energy, cost, carbon)
- Hourly simulation using DOE-2.1E & other methods
- 7 million site visits so far
- API now used by 3rd-party developers

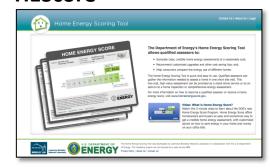
HESconsumer



HESpro

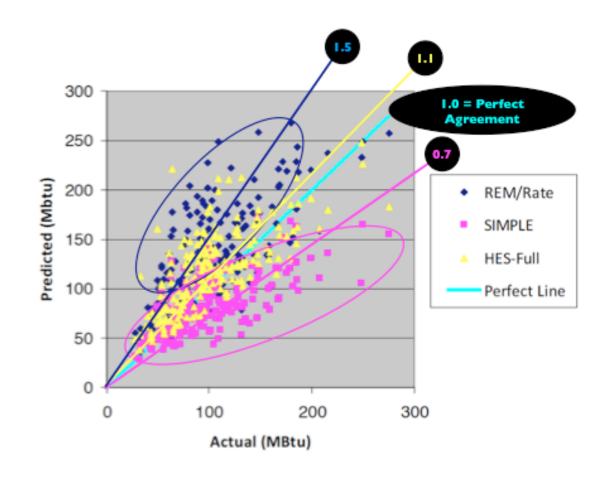


HEScore



Accuracy Misreadings

- Energy Trust of Oregon & CSG (2008) concluded that:
 - the tool in pink is more accurate than the tools in yellow & blue
 - more inputs do not make the analysis more accurate



Accuracy is Rarely Well-defined

Accuracy of What?

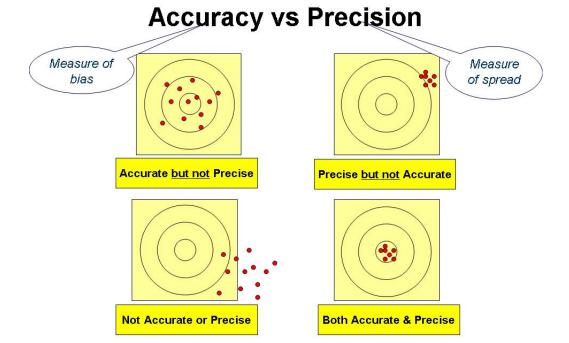
- Modeling
- Programming (bugs)
- Audit data
- Default values
- User inputs
- Measured data & weather

How is Accuracy Defined?

- Metrics
- Acceptable tolerance
- Whole-house vs. Fuel vs. End Use level
- Operational vs. Asset

Why is Accuracy Assessment being Done?

- Much depends on purpose of the analysis and how results are to be used
- Accuracy assessments are most valuable when used during model development vs after the fact



Asset vs. Operational Assessment

- Asset assessment (low information "drive-by" audit)
- Operational: classic on site energy audit
- This study focuses on Operational analyses
 - see Bourassa et al.
 for accuracy results
 of the Asset-based
 derivative of HES =>
 HEScore

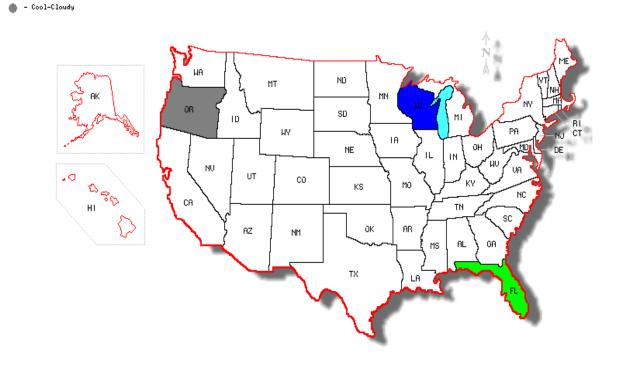




Model Accuracy Across Climates

Geographic variation of HES Accuracy

- Operational analysis: 428 homes (QA'd down from 660)*
 - FSEC & NREL Data
- Model results compared to actual energy data
- Three climates
 - Florida (Hot Humid) – 2 cohorts
 - Wisconsin (Cold)
 - Oregon (Cool/ Cloudy)



^{*} See https://sites.google.com/a/lbl.gov/hes-public/accuracy/decision-rules

Four Scenarios of Input Detail

- "Defaults" = fully defaulted, except for weather
 - inputs: 1 required 0 optional]
- "Asset::Visual" = nonintrusive, non-instrumented
 - Inputs: 18 required 9 optional
- "Asset::Full" = Instrumented audit; more equipment & envelope characteristic data
 - Inputs: 26 required 16 optional
- "Operational" = Asset::Full + behavioral inputs (interview)
 - Inputs: 28 required; 29 optional



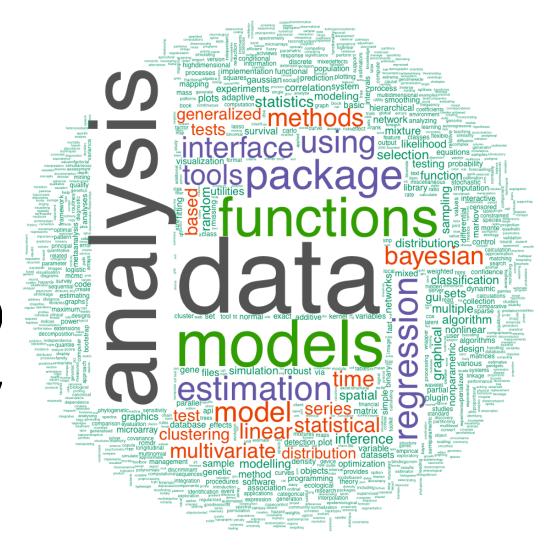






Caveats

- Even the "Operational" scenario was limited in rigor (lighting and misc. appliances poorly characterized in audits)
- Mapping good fieldaudit data to model inputs is challenging (e.g., duct locations and conditioned basements)
- Not all behavioral factors could be directly accommodated in the model (e.g., vacancy; zoned heating/cooling; use of MELs)



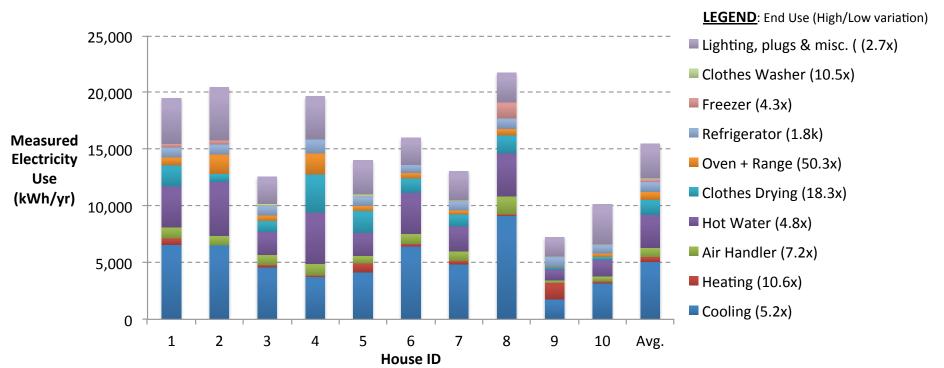
Cohort Characteristics and HES Summary Results for the Four Cohorts of Homes

	FL: Homestead	FL: Florida Power Corp	Wisconsin	Oregon
Sample size	10 homes	171 homes	139 homes	108 homes
Defaults	-15%	-19%	4%	66%
Asset:: Visual	-17%	-7%	68%	56%
Asset::Full	-25%	-5%	7%	19%
Operational	0.5%	1.3%	na	-0.4%

Precision of the results (CV) was also best in each of the Operational cases

Homestead Cohort: Virtually identical Homes & Efficiencies... ... but 3x Variation in Energy Use

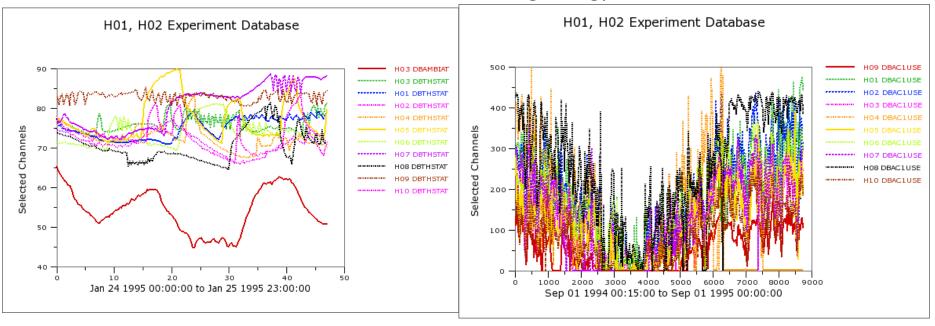
- Even greater differences at end-use level
- End-use data extremely valuable for forensic accuracy assessment



We Benefitted from High-fidelity Interval Data for the Homestead Houses

Interior Temps: Jan. 24- 25th, 1995

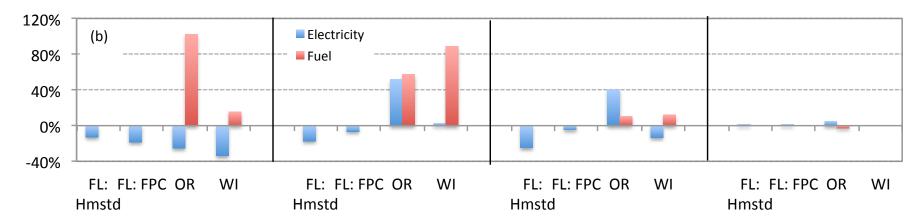
Heating Energy Use: Jan. 24th-25th, 1995



More at https://sites.google.com/a/lbl.gov/hes-public/accuracy/submetered-data

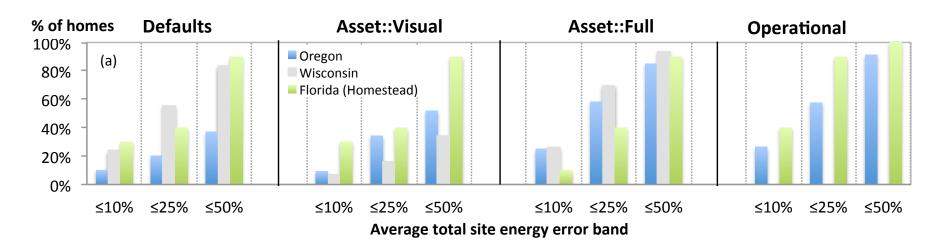
HES Accuracy by (a) Fuel & (b) #Inputs

"Accuracy" can arise from offsetting errors



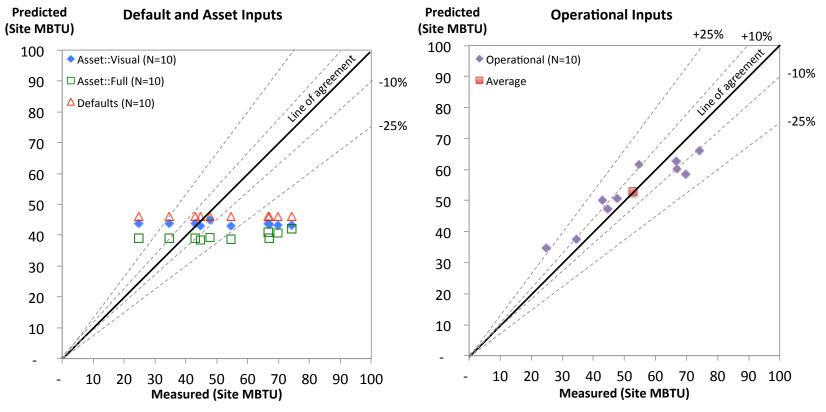
Florida homes are all-electric

More inputs <u>can</u> improve accuracy



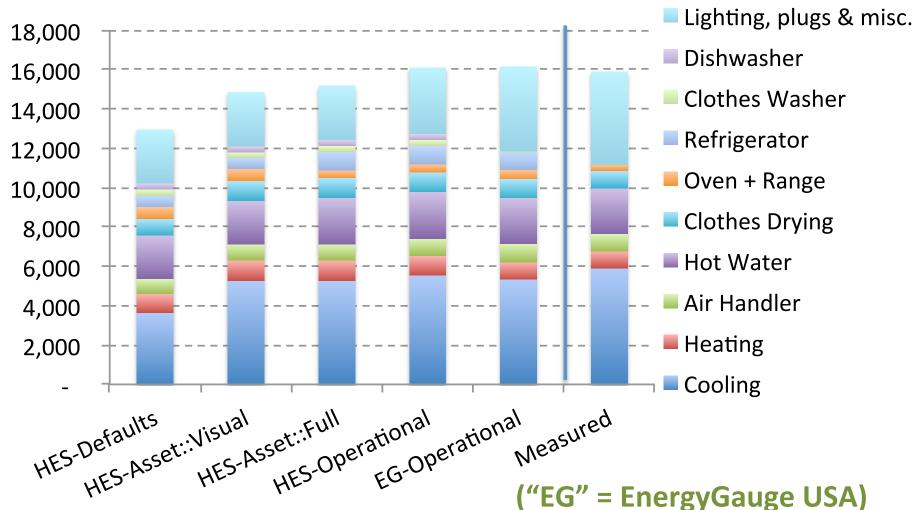
Measured vs. HES-predicted Annual Energy Use: Homestead Cohort

- Asset analysis good on average; but often lousy for specific home
- Operational analysis accurate within 1% (avg)



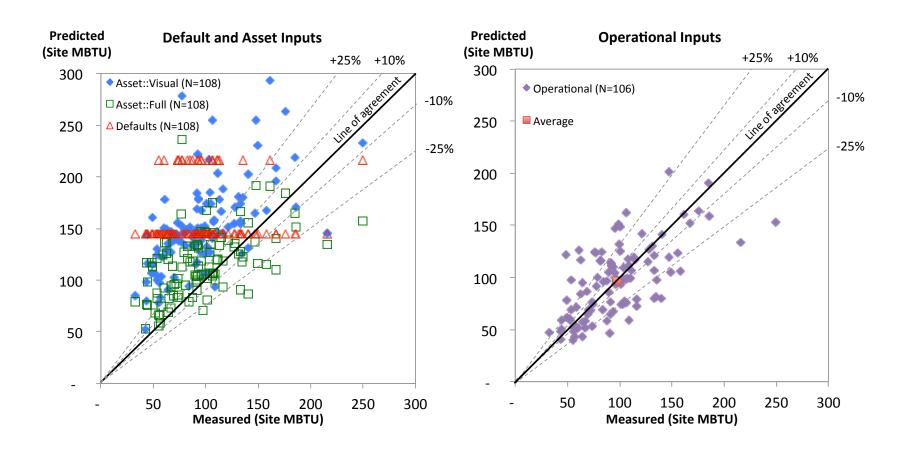
Results by End Use: Central Florida Large Sample





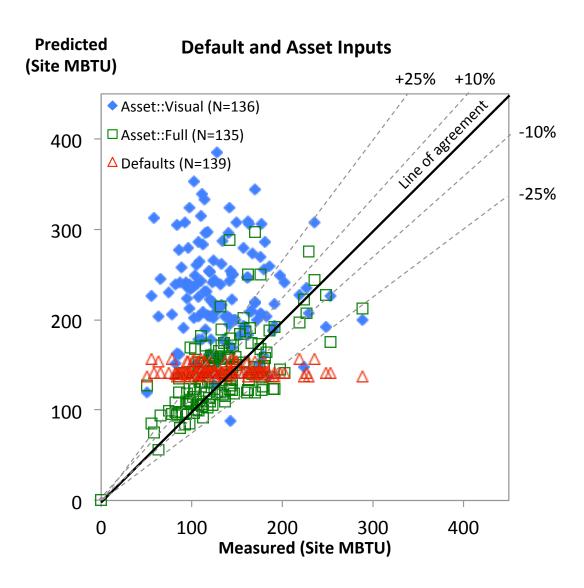
Measured vs. HES-predicted Annual Energy Use: Oregon Cohort

- Asset runs high, improve with increased inputs
- Operational runs accurate to within 1% (avg)



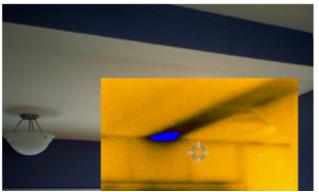
Measured vs. HES-predicted Defaults and Asset Annual Energy Use: Wisconsin

- Asset runs
 good with Full
 inputs (w/in
 7% on avg)
- Data did not support full operational analysis



Value of Accuracy Assessment During Tool Development

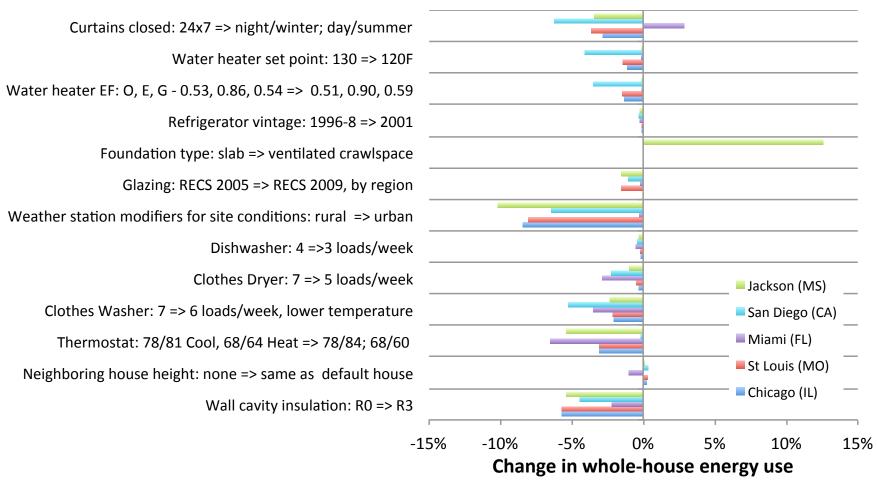
- Powerful: Compare measured data to model predictions vs. house and equipment characteristics
- Identified bug in air handler/AC algorithm: results went from 75% under-prediction to 1% overprediction in Florida home sample
- Identified need for updates to duct model, and inappropriate treatment of regain
- Identified and repaired inappropriate free heat from certain appliances (e.g. clothes dryer venting)
- Improvements/updates to defaults, reflecting current housing stock





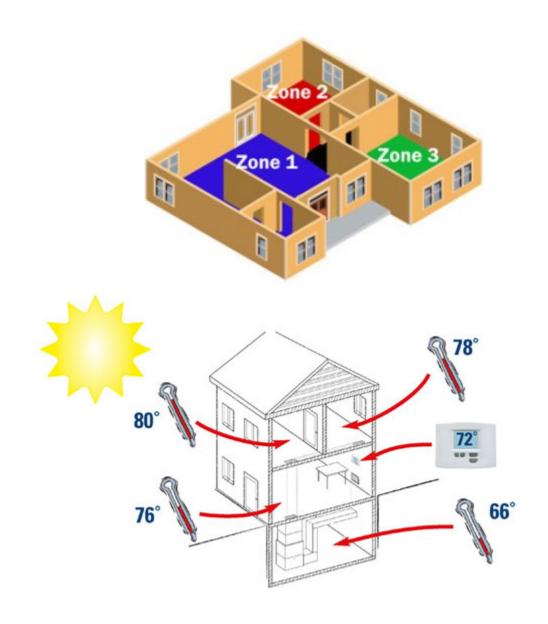
Defaults Assumptions are Important

Sensitivity of HES-predicted whole-house
 Energy Use to old vs new default assumptions



Future Simulation Enhancements

- Influence of partition walls: interior walls in poorly insulated homes provides significant increases in overall thermal resistance
- Zoning: GRI evaluation in 1980 revealed 30% reduction in heating from zoned vs. central
- Degree of basement conditioning
- Updates to duct model with treatment of regain
- Window heat transfer from curtains/insect screening (empirical & laboratory data)
- Critical inputs emphasis in revised user interface





- HES Pro: Operational factors brings accuracy to < 1% of actual bills, on average
 - Minimizes variance relative to asset analyses
 - Accuracy found to be excellent, even at the end-use level
 - Repeatability results in large samples in varied climates
- Operational factors have as great an effect on accuracy as do physical characteristics
 - How occupant operates the house matters at least as much as the house construction and equipment. Major conclusion!
- Deficiencies or gaps in audit data erode perceived accuracy
 - Lighting and miscellaneous energy use are important
- Accuracy assessments (prediction vs. data) aid model development
 - Errors often offset one-another; can give false illusion of accuracy
 - End-use data particularly useful to address such issues
- Building simulation community now capturing important nuances (e.g., basement thermal performance)
- Improved modeling of lighting/miscellaneous energy and zoning are important to further improvements in accuracy

